

1 Inferring soil moisture memory from streamflow
2 observations using a simple water balance model

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Abstract

Soil moisture is known for its integrative behavior and resulting memory characteristics. Soil moisture anomalies can persist for weeks or even months into the future, making initial soil moisture a potentially important contributor to skill in weather forecasting. A major difficulty when investigating soil moisture and its memory using observations is the sparse availability of long-term measurements and their limited spatial representativeness. In contrast, there is an abundance of long-term streamflow measurements for catchments of various sizes across the world. We investigate in this study whether such streamflow measurements can be used to infer and characterize soil moisture memory in respective catchments. Our approach uses a simple water balance model in which evapotranspiration and runoff ratios are expressed as simple functions of soil moisture; optimized functions for the model are determined using streamflow observations, and the optimized model in turn provides information on soil moisture memory on the catchment scale. The validity of the approach is demonstrated with data from three heavily monitored catchments. The approach is then applied to streamflow data in several small catchments across Switzerland to obtain a spatially distributed description of soil moisture memory and to show how memory varies, for example, with altitude and topography.

³³ 1 Introduction

³⁴ Among the variables of the climate system, soil moisture has potentially important memory (per-
³⁵ sistence) characteristics. If soil moisture anomalies, as induced by precipitation anomalies, persist
³⁶ into subsequent weeks, and if these long-lasting anomalies are then translated to the atmosphere
³⁷ through their impacts on the surface energy balance, soil moisture memory may have profound
³⁸ implications for climate variability and prediction.

³⁹ The role of soil moisture memory in climate, however, is still not completely understood. Complex-
⁴⁰ ity arises, for example, from the fact that while a soil moisture persistence signal can be translated
⁴¹ to the atmosphere through evaporation anomalies (i.e., through soil moisture-evapotranspiration
⁴² coupling and land-atmosphere interactions), these evaporation anomalies in turn act to reduce
⁴³ any original soil moisture anomaly; that is, a soil moisture anomaly, when it affects the surface
⁴⁴ fluxes, also acts to limit its own lifetime (although positive feedbacks with precipitation could
⁴⁵ also enhance it, e.g. *Koster and Suarez* 2001). In considering this balancing act, it is instructive
⁴⁶ to consider two competing and extreme scenarios. In the first scenario, evaporation processes
⁴⁷ annihilate a soil moisture anomaly within a day or two of its formation; soil moisture memory
⁴⁸ would then be small, and its effects on climate variability would necessarily be minimal. In the
⁴⁹ second scenario, the soil moisture anomaly does not affect evaporation or runoff and thereby
⁵⁰ persists indefinitely; here again, because the atmosphere or rivers cannot feel the anomaly, im-
⁵¹ pacts on climate variability would necessarily be small. Evidence exists to show that neither of
⁵² these extremes wholly captures the way nature works. In many regions, an important middle
⁵³ ground is achieved: soil moisture anomalies have been observed to persist for weeks to months
⁵⁴ (*Vinnikov and Yeserkepova* 1990, *Entin et al.* 2000, *Seneviratne et al.* 2006), and their impacts
⁵⁵ on atmospheric variability do indeed manifest themselves at those timescales, as demonstrated
⁵⁶ by various studies which quantify the impact of soil moisture initialization on the skill of sub-
⁵⁷ seasonal precipitation and/or temperature forecasts (e.g., *Viterbo and Betts* 1999, *Koster et al.*

58 2004, *Douville* 2010, *Koster et al.* 2010b, *Seneviratne et al.* 2010) or identified lag correlations
59 between surface moisture deficits and temperature extremes (e.g., *Hirschi et al.* 2011, *Mueller*
60 and *Seneviratne* 2012). This memory, at the same time, also allows soil moisture initialization to
61 contribute significant skill to seasonal streamflow forecasts (e.g., *Koster et al.* 2010a, *Mahanama*
62 *et al.* 2012).

63 The existence of this useful middle ground makes soil moisture memory worthy of careful
64 study. A critical step in this understanding is the characterization of memory and its variations
65 across the globe. Unfortunately, such a characterization is not straightforward. A major obstacle
66 is the limited availability of long-term soil moisture measurements (e.g. *Robock et al.* 2000,
67 *Seneviratne et al.* 2010, *Dorigo et al.* 2011). Ground measurements of soil moisture are only
68 available at the point scale, which implies some limitation in their spatial representativeness.
69 Although spatial variability should not be overstated (e.g. *Mittelbach and Seneviratne* 2012),
70 different hydrological dynamics may be active, for example, over adjacent grassland and forest
71 areas (*Teuling et al.* 2010b, *Orth and Seneviratne* 2012a). Also, model estimates of soil moisture
72 cannot be used for persistence studies, given the dependence of simulated soil moisture persistence
73 on generally unvalidated model assumptions.

74 In contrast, streamflow measurements are widely available, they generally cover longer periods,
75 and they represent an integral of hydrological processes over an area. Because streamflow itself
76 responds to soil moisture variations (see also *Kirchner* 2009 and *Mahanama et al.* 2012), it is
77 natural to ask whether streamflow measurements contain useful information on catchment-scale
78 soil moisture anomalies and soil moisture memory. We address this question in this paper. Using
79 an adaptation of the simple water-balance model of *Koster and Mahanama* (2012), streamflow
80 measurements are translated into fitted functional relationships between soil moisture and both
81 runoff and evapotranspiration. These fitted relationships in turn provide estimates of soil moisture
82 memory. The approach is successfully validated in three heavily monitored catchments in central

83 Europe and is then applied to several near-natural catchments in Switzerland, providing a spatial
84 picture of how soil moisture memory varies across the country. The analysis shows how soil
85 moisture memory is affected by both, geomorphological controls (e.g., altitude, topography, and
86 catchment size) as well as meteorological controls (e.g., dryness index and the potential for
87 externally-induced memory from the atmospheric forcing to be transmitted into the soil).

88 2 Methodology

89 2.1 Simple Water-balance Model

90 *Koster and Mahanama (2012)* (hereafter referred to as KM12) developed a simple water-balance
91 model to study the influence of soil moisture on hydroclimatic means and variability on large
92 spatial and temporal scales. We use a similar approach in the present study. However, because
93 we focus here on soil moisture memory in small catchments on daily to weekly time scales, we
94 introduce several new features to the model, as described below.

95 2.1.1 Water Balance Equation

96 As in KM12, the model used here is based on the following water balance equation:

$$97 \quad w_{n+\Delta t} = w_n + (P_n - E_n - Q_n) \Delta t \quad (1)$$

98 where w_n denotes the model's sole prognostic variable: the total soil moisture content (in mm)
99 at time step n . The value of w_n is altered by precipitation P_n , evapotranspiration E_n , and runoff
100 Q_n (all in $\frac{mm}{d}$) accumulated from time step n to $n + \Delta t$ to yield the soil moisture at the next
101 time step, $w_{n+\Delta t}$. As in KM12, we run the model here with a time step of one day ($\Delta t = 1d$).

102 2.1.2 Evapotranspiration

103 As in KM12, we assume simple dependencies of evapotranspiration (normalized by net radiation
104 (in $\frac{W}{m^2}$)) and runoff (normalized by precipitation) on soil moisture. We use the following equation
105 to capture the control of soil moisture on the ratio of evapotranspiration to net radiation, or ET
106 ratio:

107

$$\frac{\lambda \rho_w E_n}{R_n} = \beta_0 \left(\frac{w_n}{c_s} \right)^\gamma \text{ with } \gamma > 0 \text{ and } \beta_0 \leq 1 \quad (2)$$

108 where λ is the latent heat of vaporization (in $\frac{J}{kg}$) and ρ_w is the density of water (in $\frac{kg}{m^3}$). Soil
109 moisture is scaled by the soil water holding capacity c_s (in mm) so that the function operates on
110 the degree of saturation (unitless). The unitless exponent γ ensures that the function is strictly
111 monotonically increasing, so that the ET ratio increases with soil moisture. The factor β_0 (also
112 unitless) reflects the residual plant and soil evaporative resistance under conditions which are not
113 soil moisture-limited (e.g. *Seneviratne et al.* 2010). This factor therefore prevents the complete
114 conversion of available net radiation into ET even when water is fully available (reflecting, for
115 example, the fact that even with no water stress, transpiring water must still travel through the
116 vegetation).

117 2.1.3 Runoff and streamflow

118 Even if runoff in nature is controlled by many variables, we assume that it depends on precipitation
119 and soil moisture only, according to the equation:

120

$$\frac{Q_n}{P_n} = \left(\frac{w_n}{c_s} \right)^\alpha \text{ with } \alpha \geq 0 \quad (3)$$

121 As with the exponent γ in (2), the unitless exponent α ensures that the runoff ratio $\frac{Q_n}{P_n}$ increases

122 monotonically with soil moisture. Note that runoff as defined here (which includes, in effect, both
 123 overland flow and drainage to baseflow-producing groundwater) is distinct from streamflow, as
 124 measured at a stream gauge site; the latter quantity includes delays associated with the subsurface
 125 water transport to the streambeds and the transport of the surface water to the stream gauge
 126 site. Based on sensitivity tests, we found that accounting explicitly for this distinction between
 127 runoff and streamflow improves the model's performance in comparison to the KM12 version
 128 (not shown). We thus compute streamflow from the simulated runoff values by imposing a delay
 129 characterized by a timescale τ :

130

$$S_{n+t} = Q_n \frac{1}{\tau} e^{-\frac{t}{\tau}} \quad (4)$$

131 where the streamflow S_{n+t} corresponds to the streamflow produced at time $n + t$ associated with
 132 the surface runoff formed at time n . The integral of $\frac{1}{\tau} e^{-\frac{t}{\tau}}$ as $t \rightarrow \infty$ equals 1, ensuring that the
 133 full complement of assumed runoff water (i.e., $P_n \left(\frac{w_n}{c_s}\right)^\alpha$, from Equation (3)) does contribute to
 134 streamflow at some time. The parameter $\frac{1}{\tau}$ determines how quickly the runoff is transformed into
 135 streamflow, whereas τ corresponds to the recession time scale, expressed in days. Using Equation
 136 (4), the streamflow accumulated over the m -th time step after the precipitation event is:

137

$$S_{n+m\Delta t} = \left(\frac{w_n}{c_s}\right)^\alpha P_n \int_m^{m+\Delta t} \frac{1}{\tau} e^{-\frac{t}{\tau}} dt = Q_n \left(e^{-\frac{m\Delta t}{\tau}} - e^{-\frac{(m+1)\Delta t}{\tau}} \right) \quad (5)$$

138 With this equation we can express the streamflow at any time step as the accumulation of the
 139 effects of all runoff amounts generated during the preceding 60 time steps:

140

$$S_n = \sum_{i=0}^{60} Q_{n-i\Delta t} \left(e^{-\frac{i\Delta t}{\tau}} - e^{-\frac{(i+1)\Delta t}{\tau}} \right) \quad (6)$$

141 Note that in order to make sure that all the generated runoff is transformed into streamflow, we
 142 would in principle need to use an infinite number of time steps. Sixty time steps is an arbitrary
 143 but tractable number that allows us to account for 99% or more of the runoff water.

144 **2.1.4 Model Integration**

145 Assuming that values for the five parameters in Equations (2) and (6) (namely, c_s , β_0 , γ , α ,
 146 and τ) can be determined, Equation (1) can be driven with daily values of precipitation and net
 147 radiation over any time period of interest to produce daily time series of total soil moisture, w_n , as
 148 well as daily time series of runoff and ET. In contrast to KM12, who used monthly precipitation
 149 observations (equally distributed across the days of a given month) and an observed seasonal
 150 climatology of net radiation to force their model, we employ daily observations of precipitation
 151 and radiation. Unlike KM12, we do not include a snow layer in the model as our study focuses
 152 on the growing season.

153 In fact, due to the limitation of using a daily (rather than a finer) time step, we integrate
 154 instead an implicit form of Equation (1), a form that effectively computes the evaporation and
 155 runoff for a given day based on the soil moisture content at the end of that day:

156

$$w_{n+\Delta t} - w_n = P_n - E_{n+\Delta t} - Q_{n+\Delta t} \approx \frac{P_n - E_n - Q_n}{1 + E'_n + Q'_n} \quad (7)$$

157 where the prime (') indicates the derivative with respect to soil moisture, evaluated at w_n . Note
 158 that even with this correction, the time-discretized equation is still not perfectly solved because
 159 the functions $E(w)$ and $Q(w)$ are not linear but (partly strongly) curved.

160 Running the model requires the initialization of the soil moisture prognostic variable. We
161 spin-up the model by integrating it over five years prior to the start of a simulation.

162 **2.2 Optimization of streamflow, runoff and evapotranspiration parameters**

163 We optimize the above model with daily data from 16 European catchments, three of which have
164 been previously examined in *Orth and Seneviratne* (2012a) (hereafter referred to as OS12). We
165 use precipitation and radiation observations in these catchments to force the model. We then
166 identify, separately for each catchment, the optimal set of values for the 5 parameters in Equations
167 (2) and (6), that is, the set of values that allows the modeled streamflow S_n (Equation (6)) to
168 agree most closely with observed streamflow.

169 The accuracy of the modeled streamflow is measured with a time correlation against observed
170 streamflow. The correlation period is limited to July through September to avoid any impact of
171 snow, which is not included in the model (May-September for warmer site San Rossore). The
172 absence of snow is supported by daily average temperatures that are always above 0 degrees Celsius
173 during the correlation period. Note that while applied here to specific basins in Switzerland, the
174 simple water balance model is generally applicable to any region and time period where streamflow
175 is present.

176 One way to find the optimal set of values for the five parameters at each catchment would
177 be to run the model using all possible combinations of values. Capturing the optimal values in
178 this way with some accuracy, however, would be computationally prohibitive. To work around this
179 problem, we developed an alternative procedure (see Appendix A) to reduce the number of model
180 runs required to yield a reliable optimal parameter set (see Table 1).

181 **2.3 Validation of approach: Soil moisture memory**

182 The time series of simulated soil moisture produced with the optimal parameters, a reflection of
183 precipitation, radiation and streamflow information only, is compared to the observed soil mois-
184 ture in three highly monitored catchments to demonstrate that the precipitation, radiation, and
185 streamflow data can indeed be translated into useful information on local soil moisture behavior.

186 Because observed soil moisture information was not used at all in the calibration exercise, this
187 comparison serves as a valid test of our methodology.

188 The validation focuses in particular on soil moisture persistence. There are many ways of quantify-
189 ing soil moisture persistence; here, we compute it, for a given time of the year, as a lag correlation
190 for a given lead (see *Koster and Suarez* 2001, *Seneviratne and Koster* 2012, and OS12) that
191 ranges between 0 (no memory) and 1 (maximum memory). The memory we compute at a given
192 day with a given time lag is defined as:

$$\rho(w_n, w_{n+t_{lag}}) = \frac{cov(w_n, w_{n+t_{lag}})}{\sigma_{w_n} \sigma_{w_{n+t_{lag}}}} \quad (8)$$

193 where $cov(w_n, w_{n+t_{lag}})$ denotes the covariance between soil moisture at days n and $n + t_{lag}$ in all
194 considered years and σ_{w_n} refers to the standard deviation of soil moisture at day n using also the
195 values of all considered years. Due to the limited available number of years of soil moisture obser-
196 vations (see Section 3.1), we in fact do some smoothing of the calculated persistences, computing
197 representative estimates for half-monthly intervals. To determine the smoothed persistence for
198 a given half-monthly interval, we use a "moving window" approach (OS12) that also considers
199 the 30 days prior to the half-monthly interval and the 30 days after the end of the half-monthly
200 interval. This can be expressed mathematically as:

201

$$\rho(w_n, w_{n+t_{lag}}) = \text{trimmed average} \left(\sum_{i=t_{start}-30}^{t_{end}+30-t_{lag}} \rho(w_i, w_{i+t_{lag}}) \right) \quad (9)$$

202 where t_{start} and t_{end} refer to the beginning and end of the particular half-monthly time period.
203 The memory of that half monthly interval is then computed as a trimmed average of the $75 - t_{lag}$
204 individual persistences, avoiding days with the 10% largest and 10% lowest values (this last step
205 differs from the approach of OS12, who take the median).

206 We compute the correlation for many different lags (from 1 to 40 days) in order to capture more
207 completely the character of the persistence. One region may show high correlations at small lags
208 and a rapid fall-off in correlation at longer lags, and another may show a fast fall-off at short
209 lags and a slower fall-off thereafter; our computations will capture such differences in behavior.
210 Thus, we calculate, from both observations and the simulations with optimized parameters, the
211 correlation between soil moisture on a given date n with that at a later date $(n + t_{lag})$ across
212 all years (Equation (9)). By computing a separate correlation for each date across all years,
213 we avoid examining artificial memory associated with the climatological seasonal cycle of soil
214 moisture. The higher the resulting correlation over a prescribed lag time, the higher we deem
215 the soil moisture memory at that lag, and vice versa. Soil moisture memory is always decreasing
216 with increasing time lag, because accumulated precipitation, runoff and ET alter the soil moisture
217 content (Equation (1)). To facilitate the interpretation of soil moisture memory expressed as
218 lag correlation, *Orth and Seneviratne* (2012b) compared the lag correlation with a persistence
219 time scale (computed as mean duration to recover from anomalous conditions exceeding a certain
220 threshold to normal conditions, expressed in days). They report an exponential relationship, i.e.
221 the persistence time scale changes exponentially with linearly changing lag correlation.

222 Similarly to (9), but without time lag, we compute estimates for the standard deviations of e.g.
223 initial soil moisture over all estimates of day n of all years. Using the moving window approach we
224 obtain a number of estimates of which we take a trimmed average as a representative estimate
225 for a particular half monthly interval.

226 Soil moisture persistences in this study are computed from April to October to exclude the

²²⁷ impact of snow cover, which is not included in the model. We therefore apply the model in an
²²⁸ extended period compared to the period July-September used for optimization to allow us to
²²⁹ show that the model also performs reasonably in months that are not used for calibration, but
²³⁰ that are still mostly snow-free (underlined by daily average temperatures above 0 degrees Celsius
²³¹ on almost all days).

²³² To compute uncertainties of the soil moisture memory estimates, we separate the whole time
²³³ period (24 years, see Section 3.2) into non-intersecting subsets of 3 years (period July-September
²³⁴ in each year as described in Section 2.2) and optimize the model in each catchment to yield one
²³⁵ parameter set per subset for a particular catchment. This is done with 5 repetitions for each
²³⁶ subset (instead of 20 used for the whole time series) due to computational constraints. We apply
²³⁷ all parameter sets of a particular catchment with the whole time series and derive respective
²³⁸ soil moisture memories; from these memories we then compute the standard deviations for every
²³⁹ considered month and lag time.

²⁴⁰ 3 Data

²⁴¹ 3.1 Data analyzed for model validation

²⁴² To validate the model, we use data from the three heavily monitored catchments: Oensingen
²⁴³ (Switzerland), Rietholzbach (Switzerland) and San Rossore (Italy). The climate at the Swiss sites
²⁴⁴ is temperate humid, whereas San Rossore is characterized by Mediterranean climate. Along with
²⁴⁵ the stream gauge measurements for the full catchments, there is a site in each catchment where
²⁴⁶ ET, radiation and precipitation have been recorded. Detailed information on the catchments and
²⁴⁷ sites is provided in Table 2.

²⁴⁸ ET at Rietholzbach was measured using a weighing lysimeter (*Seneviratne et al. 2012*), whereas
²⁴⁹ the eddy-covariance flux measurement method (*Baldocchi et al. 2001*) was used at the other two
²⁵⁰ sites. As this latter method is known for its energy-balance closure error (e.g. *Wilson et al. 2002*,

²⁵¹ *Foken et al. 2006, Franssen et al. 2010*), we corrected the ET data with the following procedure:
²⁵² Using hourly values, we increased sensible and latent heat flux to equal net radiation while keeping
²⁵³ the Bowen ratio constant (*Twine et al. 2000*). If the Bowen ratio was negative both fluxes were
²⁵⁴ adjusted with respect to the strength of their dependence on net radiation instead. This strength
²⁵⁵ was the slope obtained from the regression of all available values of the particular flux against
²⁵⁶ net radiation on a particular time of the day; the flux with the higher slope was modified by the
²⁵⁷ larger fraction of the energy balance deficit. Note that the ET data from San Rossore could not
²⁵⁸ be corrected as no data of sensible heat flux is available for that site. Furthermore, we linearly
²⁵⁹ detrended the soil moisture data from Rietholzbach to address a known problem with the sensors
²⁶⁰ there (see also *Seneviratne et al. 2012*).

²⁶¹ At all three catchments, we use satellite-derived net radiation data obtained from the NASA/GEWEX
²⁶² SRB project (http://eosweb.larc.nasa.gov/PRODOCS/srb/table_srb.html [checked on 26 March
²⁶³ 2012]). Since these data only extend until 2007, we had to extrapolate net radiation from the
²⁶⁴ available solar radiation measurements for the remaining 3 years at San Rossore. These were
²⁶⁵ scaled to match the mean and standard deviation of the satellite net radiation of the previous 4
²⁶⁶ years. To evaluate the impact of this treatment we also applied such a scaling to solar radiation
²⁶⁷ measured at Oensingen and found only minor impacts on the results there, predominantly on ET
²⁶⁸ (not shown).

²⁶⁹

²⁷⁰ 3.2 Data used for model application

²⁷¹ Following validation, we apply the model to 13 near-natural catchments (i.e., catchments with
²⁷² little or no known human impact on streamflow) across Switzerland for which detailed stream
²⁷³ gauge data are available. The catchments are located in a humid temperate climate, except for
²⁷⁴ the Cassarate catchment in southern Switzerland where the climate is rather Mediterranean. A

²⁷⁵ summary of the catchment characteristics is provided in Table 3. The time period considered is
²⁷⁶ 1984-2007.

²⁷⁷ For this period, we also obtained catchment-specific precipitation and radiation data. Precip-
²⁷⁸ itation forcing for the model was derived from several MeteoSwiss (Swiss Federal Office of Mete-
²⁷⁹ orology and Climatology) rain gauges in and/or near each respective catchment. The number of
²⁸⁰ rain gauges per catchment depends on the size of the respective catchment and on the density of
²⁸¹ the network in the particular region (see <http://www.meteoschweiz.admin.ch/web/de/klima/messsysteme/boden.Par.0049.DownloadFile.tmp/karteniederschlagsmessnetz.pdf> [checked on 6 Febru-
²⁸² ary 2013]). The measurements were weighted inversely according to their distance from the catch-
²⁸³ ment in order to compute an area-representative estimate. As only solar radiation was measured
²⁸⁴ at the ground, we used net radiation data from the NASA/GEWEX SRB project. A comparison of
²⁸⁵ anomalies of the solar radiation measured at the ground with that from SRB showed correlations
²⁸⁶ between 0.8 and 0.9 for the different catchments, underlining the good match also reported by
²⁸⁷ OS12.

²⁸⁸ In order to study the dependency of soil moisture memory on topography (hilliness), we
²⁸⁹ obtained values of mean compound topographic index (CTI; *Moore et al. 1993*) from the HYDRO-
²⁹⁰ 1K dataset [<http://webgis.wr.usgs.gov/globalgis/metadataqr/metadata/hydro1k.htm>]. As a
²⁹¹ measure of topography for each catchment, the CTI is a function of slope as well as upstream
²⁹² contributing area and increases with decreasing hilliness. Note that CTI is only evaluated at the
²⁹³ catchments used for application of the model and not at the three validation catchments that
²⁹⁴ include the very small Rietholzbach catchment. Therefore the 1km x 1km resolution is sufficient
²⁹⁵ to characterize, to first order, the CTI amongst the catchments examined.

297 **4 Results**

298 In this section we first describe the application and validation of the simple model methodology
299 in three heavily monitored catchments (Sections 4.2 and 4.3). We show its satisfactory ability
300 to yield a realistic soil moisture memory despite its simplicity. In Section 4.4 we describe the
301 application of the model in multiple catchments across Switzerland. This allows us to study the
302 main meteorological controls of soil moisture memory as well as its dependency on altitude and
303 topography.

304

305 **4.1 Streamflow, runoff and evapotranspiration parameters**

306 To summarize our methodology, we optimize the applied simple water balance model (i.e., we find
307 optimized values for its five parameters) so that it reproduces well the time variations in the daily
308 streamflows measured in a given catchment when forced with local precipitation and net radiation
309 data. An overview of the fitted parameters in all catchments is provided in Table 4.

310 A note about the parameter search is appropriate here. Two parameters, the ET ratio exponent
311 and maximum ET ratio, collide with their bounds in 2 and 9 catchments, respectively, out of
312 the 16 catchments considered in total in this study (see Table 1 for bounds and Table 4 for
313 fitted parameters). Concerning the maximum ET ratio, the fact that the optimum value of β_0
314 is found to be exactly 1, an imposed bound for the parameter, does not reflect poorly on the
315 parameter estimation approach; the optimized value of 1 simply means that for the catchment in
316 question, all of the net radiation is converted to evaporation in wet conditions, a physically plausible
317 scenario. Our requirement that β_0 cannot exceed 1 is simply a reflection of our assumption that
318 net radiation provides the energy needed for evaporation. Whereas high maximum ET ratios are
319 not surprising in a radiation-limited regime that is characteristic for Switzerland, we note the
320 possibility that in nature, ET might (temporarily) exceed net radiation through processes that

321 are not captured by our simple model, such as energy input from warm air advection to Europe;
322 therefore, the collisions experienced with the β_0 term can be said to reflect the limitations of our
323 assumption. Note that both parameters that collide with their bounds are related to radiation
324 (Equation 2) and streamflow (through optimization procedure, see Section 2.2). Therefore it is
325 furthermore possible that these collisions are due to scale discrepancies between radiation and
326 streamflow measurements and the consequent mismatch in their temporal evolutions. However,
327 the parameter collisions should, in any case, not have a major impact on the resulting estimated
328 soil moisture memory as indicated by supplemental tests (not shown) in which the bounds were
329 removed (in conflict with the model's underlying assumptions) and the results were found to be
330 generally similar. Furthermore we note that despite the parameter collisions we find a good match
331 between modeled and observed soil moisture memory as described in the following subsection.

332 To validate our optimization procedure, we applied it with higher (coarser) step widths for the
333 parameters and then compared the results with those obtained when all possible combinations
334 of parameters (assuming the same coarse spacing) were tested. This allowed us to compare the
335 resulting best parameter sets. Given the high computational effort the validation was done only for
336 the three catchments listed in Table 2. The best parameter sets found from both procedures were
337 identical for all three catchments (see Table 4 for parameter values), underlining the validity of
338 the approach introduced in this study. As expected due to the larger step width (lower accuracy),
339 these parameter sets yield slightly lower correlations between observed and modeled streamflow
340 compared to the parameter sets found using the default step widths (see Table 1).

341 4.2 Validation of estimated memory

342 In addition to generating realistic streamflows, the optimized model produces, as a matter of
343 course, a time series of daily soil moisture, from which soil moisture persistence measures can be
344 derived. Our methodology for converting streamflow measurements into soil moisture information

³⁴⁵ is deemed successful if the derived soil moisture persistences obtained from this time series agree
³⁴⁶ with those obtained using independent soil moisture measurements in the catchments.

³⁴⁷ This validation test was performed in each of the three catchments described in Section
³⁴⁸ 3.1. Results are shown in Figure 1. Shown for each catchment are the modeled and observed
³⁴⁹ persistences for different lags (out to 40 days) and for different times of the year (April through
³⁵⁰ October). Overall, the memory characteristics in the three catchments are well captured by the
³⁵¹ model, with a reasonable representation in each of the seasonal cycle of soil moisture memory and
³⁵² its decay with lag. The observed and simulated memory is comparatively strong at Oensingen
³⁵³ and San Rossore and weakest at Rietholzbach. The seasonal cycle of the observed memory at
³⁵⁴ San Rossore differs clearly from that of the other two sites, and this is captured by the model.
³⁵⁵ Difference plots are shown in the bottom row of the figure; there is no clear pattern of over-
³⁵⁶ and underestimation of memory in the simulation results. The relatively large difference between
³⁵⁷ modeled and observed soil moisture memory in autumn at both Rietholzbach and San Rossore is
³⁵⁸ consistent with results of OS12 (Figure 6 of that paper), who used the same atmospheric forcing
³⁵⁹ data, and derived also a clearly underestimated soil moisture memory. In this previous study,
³⁶⁰ the identified reason for this behavior was a mismatch between precipitation and soil moisture
³⁶¹ observations in autumn at these two sites. This means that the water balance is not closed with
³⁶² the employed observations, which could be due, for example, to a higher spatial variability of
³⁶³ precipitation or a stronger role of land cover in this season.

³⁶⁴ The model, using only information on locally measured precipitation, net radiation, and stream-
³⁶⁵ flow, therefore successfully captures the distinctions between the catchments in their soil moisture
³⁶⁶ memory behavior. Despite its simplicity, it captures enough of the physical processes control-
³⁶⁷ ling memory to allow the translation of streamflow information into soil moisture information.
³⁶⁸ Furthermore, the agreement in Figure 1 suggests (as does the reasonable reproduction of soil
³⁶⁹ moisture anomalies shown below) that the time behavior of the observed site-based soil moisture

370 anomalies is representative of that for soil moisture across the catchment containing the site; that
371 is, soil moisture levels may be spatially heterogeneous within a catchment but may nevertheless
372 show similar temporal dynamics. This is consistent with results from *Mittelbach and Seneviratne*
373 (2012) for Switzerland based on measurements from the Swiss Soil Moisture Experiment (SwissS-
374 MEX), which show that soil moisture dynamics have a large regional footprint in that region,
375 unlike absolute soil moisture that displays a stronger spatial variability.

376 To illustrate further the impact of the fitted parameter set on the resulting soil moisture
377 memory characteristics – in particular, to show the relative impacts on memory of the parameter
378 values and the meteorological forcing – we run the model at each of the three sites mentioned
379 above with the parameter set fitted for the particular site and also with the parameter sets fitted for
380 the other two sites. The results are displayed in Figure 2. We find that the parameter set is more
381 important for determining the resulting soil moisture memory than is the meteorological forcing.
382 There are similarities between the actually modeled memory at Oensingen and San Rossore and
383 the resulting memory when using the parameter set or meteorological forcing from another site.
384 This can be explained by the roughly similar fitted parameters (see Table 4). Generally the strong
385 sensitivity of the memory with respect to the parameter set underlines the ability of our simple
386 model framework to yield a parameter set that is related with realistic features of the studied
387 catchments.

388 4.3 Hydrological states and fluxes

389 While the main goal of the tested methodology is the extraction of soil moisture memory statistics,
390 we can also validate the soil moisture, streamflow, and evapotranspiration time series produced
391 by the optimized model against available observations in the three validation catchments. Com-
392 parisons of the observed and simulated anomalies of these quantities are provided in the top
393 three rows of Figure 3. Mean seasonal cycles have been subtracted from both the observed and

394 simulated data in order to avoid an overestimation of model skill associated with the seasonal
395 cycles inherent in the precipitation and net radiation forcing. While this subtraction also prevents
396 a proper evaluation of bias, such bias evaluations would, in any case, be of limited usefulness: (i)
397 significant biases are likely in the observed evaporation data given the closure problem associated
398 with eddy covariance measurements (see Section 3.1), (ii) biases in soil moisture are likely because
399 the model uses an arbitrary wilting point (which doesn't affect the temporal variability of the soil
400 moisture it produces), (iii) observed absolute soil moisture is also expected to vary strongly even
401 on small spatial scales, only the temporal dynamics should display a regional footprint (*Mittel-*
402 *bach and Seneviratne 2012*), and (iv) biases in streamflow may occur especially in flat catchments
403 through baseflow out of the catchment away from the stream gauge.

404 Overall, the model seems to do especially well in estimating soil moisture variations, partic-
405 ularly for Oensingen ($R^2 = 0.78$) but also for Rietholzbach ($R^2 = 0.62$). Streamflows for these
406 two sites are also reasonably reproduced (R^2 values of 0.6 and 0.87, respectively), whereas simu-
407 lated ET values are somewhat less consistent with the observations, although still satisfactory at
408 Rietholzbach ($R^2 = 0.58$). The simulated values are always worse for the San Rossore catchment,
409 possibly due to (i) its larger size and the corresponding reduction in the large-scale representa-
410 tiveness of its site-based precipitation forcing and (ii) the interpolation of the radiative forcing (see
411 lower part of Section 3.1). In cases of comparatively low R^2 values, such as for ET at Oensingen
412 and for all quantities at San Rossore, we find that the model tends to underestimate the variability
413 of the anomalies, as indicated by the regression slopes that are clearly smaller than 1.

414 Corresponding scatter plots produced with data from June and October (not shown) show com-
415 parable agreement between the model results and observations. This provides an independent
416 evaluation of model performance, given that these months were not part of the fitting period (see
417 Section 2.2).

418 The bottom row in Figure 3 displays the optimized runoff functions (solid red lines) and ET

419 functions (solid black lines) at Oensingen, Rietholzbach and San Rossore. Every plotted point
420 represents either an observed streamflow ratio, $\frac{S_n}{P_n}$ (in red), or an observed ET ratio, $\frac{\lambda\rho_w E_n}{R_n}$
421 (in black), with the respective quantities (both the numerators and the denominators separately)
422 accumulated over a week to increase representativeness and to ensure comparability between
423 runoff ratio as shown by the fitted function and streamflow ratio as shown by the observations.

424 At first glance, the evaporation functions seem to disagree with the data. Here one must
425 remember two key points: (i) no evaporation data were used in the optimization of the functions,
426 and (ii) the evaporation observations are subject to bias and, even after bias correction, are
427 uncertain. Eddy-covariance measurements are known, for example, to produce underestimated
428 fluxes (e.g. *Wilson et al.* 2002, *Foken et al.* 2006, *Franssen et al.* 2010). Therefore we corrected
429 the ET in order to close the energy balance through a modification of latent and sensible heat fluxes
430 as described in Section 3.1. Indeed, at Rietholzbach, where ET was measured with a weighing
431 lysimeter instead, the modeled ET ratio compares better to observations. At San Rossore, the ET
432 data could not be corrected because net radiation was not available over the whole time period; the
433 observed ET fluxes there are thus underestimated. (Such errors might also explain the relatively
434 poor comparison of ET anomalies at San Rossore in the third row of Figure 3.) At Oensingen, ET
435 flux corrections may have led to excessive ratios, possibly because ET was measured over grassland
436 whereas the optimized function represents the whole catchment, which includes forested regions.
437 *Teuling et al.* (2010b), using observations, showed that forests in temperate Europe use water
438 more conservatively than grassland, especially under extreme conditions (Figure 1 of that paper).

439 In contrast, the optimized runoff functions do capture, to first order, the observed streamflow
440 ratios. This makes sense, given that the streamflow measurements were used in the optimization
441 procedure. The high fitted runoff ratio (especially for wet conditions) corresponds well with
442 the generally wet regime at Rietholzbach (annual precipitation $\approx 1500\text{mm}$), such that most of
443 the precipitation can not be stored but runs off instead. There is nevertheless still some bias
444 seen in the optimal runoff functions and a substantial amount of scatter seen in the streamflow

ratio observations. Again, our use of available streamflow and precipitation observations is made difficult by the mismatch in their scales; because the functions are optimized using data from July to September, we speculate that local thunderstorms and showers might influence parts of a catchment not captured by the rain gauge or might over-emphasize small-scale storms falling over the rain gauges. Of course, even without a scale mismatch, scatter in the plotted points will result from the fact that precipitation and streamflow measurements each have their own errors, and these errors are compounded when the ratio is computed. Again, some time shift between precipitation and streamflow is already implicitly included in Equations 4-6 through the streamflow recession.

Summing up we note that generally the unimpressive agreement found in the bottom row in Figure 3 is no surprise given the vastly different scales we consider (e.g. for streamflow and precipitation or of modeled, catchment-scale ET and observed, point-scale ET) and the noted measurement uncertainties related to, for example, eddy-covariance ET measurements or point-scale precipitation measurements. When considering this unimpressive agreement, it is worth remembering that the optimization procedure focuses on finding the runoff and evaporation functions that best reproduce the time variability of the observed streamflow (through an R^2 value), a reflection of the time dynamics of the local hydrological cycle, rather than functions that are necessarily consistent with direct evaporation and streamflow measurements, as represented by the plotted points in the lowest row of Figure 3. Naturally, if the latter approach were used, the functions chosen would agree much more strongly with those plotted points. Of course, the latter approach requires soil moisture and evaporation information, which is what we want to avoid here, given the noted dearth of contemporaneous soil moisture and evaporation data. While it is certainly possible that our optimization approach does not produce the runoff function and ET function combination that best reproduces the measured soil moisture memory, it does nevertheless produce a combination that reproduces it reasonably well (Figure 1), and it does maintain the critical advantage of being based on only streamflow, precipitation, and radiation information.

471 Note furthermore that the suitability of the optimization approach may vary depending on the
472 climate regime, as it becomes difficult, under dry conditions when streamflow variations are small,
473 to infer hydrological variability of a catchment from streamflow only (e.g. *Teuling et al.* 2010a).

474 For completeness, Figure 4 shows the hydrographs associated with the optimized values of τ
475 for the three catchments. In the Rietholzbach catchment, the streamflow response falls off most
476 quickly, as might be expected given the catchment's hilliness and relatively small size. In the other
477 two catchments, 2% of the water in a precipitation event is still running off two weeks after the
478 event.

479 4.4 Application to multiple Swiss catchments

480 The application of the methodology to precipitation, net radiation, and streamflow data in 13
481 catchments across Switzerland (Section 3.2) allows us to obtain an areal picture of soil moisture
482 memory (30-day-lagged autocorrelation), as shown in Figure 5. The similar memories found for
483 adjacent catchments, even those with different sizes, provides additional support for our approach.
484 A signature of the alpine ridge (and its associated precipitation regime) is seen in the memory
485 distribution.

486 The highest memory is found for the Langeten catchment, which is located in the Swiss plateau
487 between the Alps and the Jura mountains. High memory is also found for the Mentue (also in the
488 Swiss plateau) and Ergolz (northern end of the Jura mountains) catchments. The lowest memory
489 is found in the highest catchments: Sitter, kleine Emme, Emme and Sense. Overall, soil moisture
490 memory seems to increase with increasing distance from the Alps, as seen in the far west for
491 the Broye and Mentue catchments and in the far east for the Murg, Aach, Goldach and Sitter
492 catchments. Despite the drier climate regime south of the Alps, we find a similar strength of the
493 soil moisture memory at Cassarate compared to catchments along the northern alpine front.

494 Figures 6 and 7 summarize the results for all catchments, showing the optimized runoff and ET

495 functions (Column 1) and the corresponding soil moisture memories as a function of season and
 496 lag (Column 2). The rows holding the catchment results are arranged in order of average memory,
 497 starting with Langeten (the catchment with the strongest memory). The optimized functions differ
 498 significantly among the catchments, as does the absolute soil moisture range. Correspondingly,
 499 the strength of the estimated soil moisture memory and its seasonal cycle differ significantly across
 500 the catchments, especially in summer. In general, memory seems to be strongest in autumn, for
 501 which considerable memory is often seen at 4-5 week lags, and it is weakest in spring, which
 502 generally shows almost no significant memory beyond 2 weeks.

503 Figures 6 and 7 also display the uncertainties corresponding to the soil moisture memories,
 504 as derived with the methodology described in Section 2.3. They are mostly smaller than 0.2,
 505 indicating that the computed memory patterns are robust with respect to parameter sets obtained
 506 from different and independent subsets of the full time period analyzed. Especially if the estimated
 507 memory is high, the uncertainties are low; therefore high soil moisture memory as identified with
 508 the simple water balance model is particularly reliable.

509 4.4.1 Controls of soil moisture memory in Switzerland

510 OS12 identified two main controls of soil moisture memory at five sites in Central and Mediter-
 511 ranean Europe; (i) the ratio between the variability of initial soil moisture and subsequent forcing,
 512 and (ii) the correlation between initial soil moisture and the subsequent forcing. They also report
 513 that the forcing is dominated by precipitation, and thus we can express the first control as the
 514 unitless ratio between the standard deviation of initial soil moisture and the standard deviation of
 515 subsequent precipitation:

$$\tilde{\kappa}_n = \frac{\sigma_{w_{n,y}}}{\sigma_{P_{n,y}t_{lag}}} \quad (10)$$

516 where $P_{n,y}$ denotes precipitation (in $\frac{mm}{d}$) between date n and $n + t_{lag}$ of year y . It is multiplied
 517 with t_{lag} to yield the accumulated precipitation during that interval. The standard deviations are

518 computed as described in Section 2.3. Note that $\tilde{\kappa}_n$ also reflects the impact of seasonal variations
519 in precipitation. Given that precipitation dominates the forcing, the second control identified in
520 OS12 can be simplified to yield $\rho(w_n, P_n)$. High values of either of these controls are indicative of
521 higher soil moisture memory. The first control, $\tilde{\kappa}_n$, reflects the size of the anomaly to be erased
522 relative to that of the precipitation available to erase it, and the second describes how the effect
523 of the precipitation may be diminished if its magnitude is not independent of the initial anomaly.

524 The fourth and fifth columns of Figures 6 and 7 illustrate the values of these controls at all
525 catchments, for all months and lags considered. The ratio of the soil moisture and precipitation
526 variabilities decreases from the top to the bottom in both figures as the soil moisture memory
527 decreases, suggesting a connection. Confirming the results of OS12, also comparatively high
528 correlations between initial soil moisture and the subsequent precipitation (a reflection, indeed, of
529 memory in precipitation itself) seem to coincide with high memory in most catchments.

530 Moreover these two figures show that the runoff optimization approach (Section 2.2) yields
531 functions of similar shape for nearby catchments (e.g. Mentue/Broye and Sitter/Goldach), un-
532 derlining the robustness of the simple model approach. However, despite such similarity in the
533 functions, we can sometimes find different strengths for the soil moisture memory, as in the
534 Mentue and Broye catchments, illustrating the importance of catchment-specific parameters such
535 as water holding capacity and maximum ET ratio.

536 Figure 8 shows the correlations between the optimized model parameters and the resulting soil
537 moisture memory (as shown in Figure 5). Water holding capacity is seen to be a strong control of
538 soil moisture memory, which is intuitively sensible; it has a direct impact on the numerator of the
539 standard deviation ratio discussed above. A second control of memory is the runoff ratio exponent
540 (even if of questionable statistical significance due to the relatively small set of catchments). The
541 higher this exponent, the greater the contrast in the impact of runoff on soil moisture in wet and
542 dry conditions. That is, for a high exponent, the dampening impact of runoff on soil moisture
543 anomalies is significantly reduced in drier conditions. OS12 found that especially dry anomalies

544 contribute to a higher soil moisture memory, which explains why the runoff ratio exponent has such
545 a large effect. It is important to note that these three controls are not statistically independent,
546 for otherwise they would explain too much of the variance of soil moisture memory; a proper
547 breakdown of the roles of these parameters and how they vary with each other would require a
548 substantially larger collection of analyzed catchments.

549 4.4.2 Dependence of soil moisture memory on altitude, topography and dryness index

550 Investigating the dependency of soil moisture memory on altitude, topography and dryness index
551 allows us to separate the effects of soil and vegetation characteristics, morphology and atmospheric
552 forcing, respectively. Even if altitude and topography are usually related, here they are to some
553 extent independent due to the complex (pre-) alpine terrain of Switzerland. The top row of Figure
554 9 demonstrates that memory decreases with altitude and with increased topography (expressed as
555 CTI, see Section 3.2). The bottom row of the figure shows a link between $\tilde{\kappa}_n$ (the aforementioned
556 ratio of initial soil moisture variability to precipitation variability shown in Equation (10)) and both
557 altitude and topography. This $\tilde{\kappa}_n$ ratio was identified in Section 4.4.1 as a main control of soil
558 moisture memory, which is consistent with the shown dependencies on altitude and topography.
559 The higher (or hillier) a catchment is, the thinner the soil should be, leading to a decreased water
560 holding capacity and therefore a lower σ_{w_n} and thus a lower $\tilde{\kappa}_n$ value. Even if topography and
561 altitude are found to have the same impact on soil moisture memory, the reasons may not be
562 the same, since topography as such only impacts soil moisture dynamics whereas altitude also
563 reflects the varying atmospheric forcing (e.g. precipitation (variability) increasing with altitude
564 and thereby reducing soil moisture memory as described in the previous subsection).

565 We also investigated the link between mean soil moisture memory (as shown in Figure 5) and
566 catchment-specific dryness index, as illustrated with the plots on the right hand side of Figure 9.

567 The dryness index is computed as $\frac{\bar{R}}{\lambda \rho_w \bar{P}}$, where λ is the latent heat of vaporization and \bar{R} and

⁵⁶⁸ \bar{P} are long-term averages of annual net radiation and precipitation, respectively. Soil moisture
⁵⁶⁹ memory tends to increase with increasing dryness index, even if the diagnosed relationship between
⁵⁷⁰ the two is rather weak. Less precipitation leads to a lower variability and thus a higher $\tilde{\kappa}_n$ value
⁵⁷¹ as shown in the Figure.

⁵⁷² Comparing the influence of these three controls on soil moisture memory in Switzerland as
⁵⁷³ indicated by the R^2 values, we find that altitude is of highest importance, followed by topography
⁵⁷⁴ and dryness index.

⁵⁷⁵ 5 Conclusions

⁵⁷⁶ In this study we modified the simple water-balance model proposed by *Koster and Mahanama*
⁵⁷⁷ (2012) to include such features as streamflow recession and an implicit form of the water balance
⁵⁷⁸ equation. We then applied the model to the analysis of soil moisture memory. Our main tested
⁵⁷⁹ hypothesis was whether such a simple model can be used to extract information on soil moisture
⁵⁸⁰ memory based on observations of precipitation, net radiation, and streamflow alone, since these
⁵⁸¹ observations are much more plentiful than soil moisture observations.

⁵⁸² Our approach was successfully validated using data from some of the relatively rare catchments
⁵⁸³ for which soil moisture measurements and contemporaneous meteorological measurements are
⁵⁸⁴ adequate. Using only precipitation, net radiation, and streamflow data, the model captures the
⁵⁸⁵ first order behavior of the observed soil moisture memory in terms of its variation with season and
⁵⁸⁶ the considered lag (Figure 1). The model also reproduces the observed soil moisture anomalies
⁵⁸⁷ reasonably well (Figure 3).

⁵⁸⁸ We then used the validated model to estimate the soil moisture memory within 13 near-natural
⁵⁸⁹ catchments across Switzerland. The resulting spatial distribution of estimated memory allowed
⁵⁹⁰ an analysis of the controls on this memory. Our results support earlier propositions that the main
⁵⁹¹ controls of memory in Central Europe are (i) the ratio of the standard deviations of initial soil

592 moisture and subsequent precipitation, and (ii) the correlation between the initial soil moisture and
593 the subsequent precipitation. Soil moisture memory in the vicinity of the Alps appears to decrease
594 with altitude and hilliness (as measured by CTI), possibly because soils at higher elevations tend
595 to be thinner.

596 The study with the 13 Swiss catchments demonstrates that the simple water balance model can
597 be used in conjunction with precipitation, net radiation, and streamflow measurements to estimate
598 soil moisture memory and its controls even in the absence of direct soil moisture measurements.
599 Applying this methodology to catchments in other regions of the world could help identify areas
600 of strong soil moisture memory, that is, areas for which soil moisture initialization has a chance
601 to contribute to hydrological or meteorological prediction.

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614 **Appendix A: Optimization procedure for identification of catchment-
615 specific parameter sets**

616 We first choose a random value for each parameter in Equations (2) and (6) from within a
617 prescribed acceptable range and add a prescribed step width (see Table 1) to yield a second value
618 for each parameter. We then run the model for all $2^5 = 32$ combinations of parameters to find the
619 set which yields the highest correlation between modeled and observed streamflow. After that,
620 we rerun the model using another $2^5 = 32$ combinations, assigning to each parameter the optimal
621 value found before and this value with the respective step width subtracted (if the lower value
622 from before was the optimal value) or added (if the higher value from before was the optimal
623 value). This procedure is repeated until the same set of parameters is found two times in a row.

624 This procedure, of course, guarantees only a local (rather than a global) optimum in the five-
625 dimensional parameter space. We thus repeat the procedure 20 times, always starting with new
626 randomly chosen values for each parameter. This yields 20 local optima, of which many are similar
627 or even identical, underlining the robustness of this approach. Of these 20 local optima we take
628 the best as our parameter set for a given catchment. Our tests with the procedure suggest that
629 higher computational effort would probably not yield a different solution; given the step widths
630 applied to the parameters, we most likely indeed find the global optimum in the five-dimensional
631 parameter space.

632

634

References

635 Ammann, C., O. Marx, V. Wolff, and A. Neftel (2010), Measuring the biosphere-atmosphere ex-
 636 change of total reactive nitrogen by eddy covariance using a novel converter, in *29th Conference*
 637 *on Agricultural and Forest Meteorology*.

638 Baldocchi, D. D., et al. (2001), FLUXNET: A new tool to study the temporal and spatial variability
 639 of ecosystem-scale carbon dioxide, water vapor and energy flux densities, *Bull. Amer. Meteorol.*
 640 *Soc.*, 82, 2415–2435.

641 Dorigo, W. A., et al. (2011), The international soil moisture network: a data hosting facility for
 642 global in situ soil moisture measurements, *Hydrol. Earth Syst. Sci.*, 15, 1675–1698.

643 Douville, H. (2010), Relative contribution of soil moisture and snow mass to seasonal climate
 644 predictability: A pilot study., *Clim. Dyn.*, 34, 797–818.

645 Entin, J. K., A. Robock, K. Y. Vinnikov, S. E. Hollinger, S. Liu, and A. Namkhai (2000), Temporal
 646 and spatial scales of observed soil moisture variations in the extratropics, *J. Geophys. Res.*, 105,
 647 11,865–11,877.

648 Foken, T., F. Wimmer, M. Mauder, C. Thomas, and C. Liebethal (2006), Some aspects of the
 649 energy balance closure problem, *Atmos. Chem. Phys.*, 6, 4395–4402.

650 Franssen, H. H., R. Stöckli, I. Lehner, E. Rotenberg, and S. I. Seneviratne (2010), Energy balance
 651 closure of eddy covariance data: a multi-site analysis for European FLUXNET stations, *Agric.*
 652 *Forest Meteor.*, 150 (12), 1553–1567.

653 Hirschi, M., S. I. Seneviratne, V. Alexandrov, F. Boberg, C. Boroneant, O. B. Christensen, H. For-
 654 mayer, B. Orlowsky, and P. Stepanek (2011), Observational evidence for soil-moisture impact
 655 on hot extremes in southeastern Europe, *Nature Geoscience*, 4, 17–21.

656 Kirchner, J. (2009), Catchments as simple dynamical systems: Catchment characterization,
 657 rainfall-runoff modeling, and doing hydrology backward, *Water Resources Research*, 45,
 658 W02,429.

659 Koster, R. D., and S. Mahanama (2012), Land Surface Controls on Hydroclimatic Means and
 660 Variability, *J. Hydrometeorol.*, 13, 1604–1620.

661 Koster, R. D., and M. J. Suarez (2001), Soil moisture memory in climate models, *J. Hydromete-
 662 orol.*, 2, 558–570.

663 Koster, R. D., S. P. P. Mahanama, B. Livneh, D. P. Lettenmaier, and R. H. Reichle (2010a), Skill
 664 in streamflow forecasts derived from large-scale estimates of soil moisture and snow, *Nature*
 665 *Geoscience*, 3, 613–616.

666 Koster, R. D., et al. (2004), Regions of strong coupling between soil moisture and precipitation,
667 *Science*, 305, 1138–1140.

668 Koster, R. D., et al. (2010b), Contribution of land surface initialization to subseasonal forecast
669 skill: First results from a multi-model experiment, *Geophys. Res. Lett.*, 37, L02402.

670 Mahanama, S. P. P., B. Livneh, R. D. Koster, D. Lettenmaier, and R. Reichle (2012), Soil
671 moisture, snow, and seasonal streamflow forecasts in the United States, *J. Hydrometeorol.*, 13,
672 189–203.

673 Mittelbach, H., and S. I. Seneviratne (2012), A new perspective on the spatio-temporal variability
674 of soil moisture: temporal dynamics versus time invariant contributions, *Hydrol. Earth Syst.
675 Sci.*, 16, 2169–2179.

676 Moore, I. D., P. E. Gessler, G. A. Nielsen, and G. A. Petersen (1993), Terrain attributes: estimation
677 methods and scale effects, in: *Modeling Change in Environmental Systems*, pp. 189–214.

678 Mueller, B., and S. I. Seneviratne (2012), Hot days induced by precipitation deficits at the global
679 scale, *Proc. Natl. Acad. Sci.*, 109 (31), 12,398–12,403.

680 Orth, R., and S. I. Seneviratne (2012a), Analysis of soil moisture memory from observations in
681 Europe, *J. Geophys. Res.*, 117, D15,115, doi:10.1029/2011JD017366.

682 Orth, R., and S. I. Seneviratne (2012b), Propagation of soil moisture memory to runoff and
683 evapotranspiration, *Hydrol. Earth Syst. Sci. Disc.*, 9, 12,103–12,143.

684 Robock, A., K. Y. Vinnikov, G. Srinivasan, J. K. Entin, S. E. Hollinger, N. A. Speranskaya, S. Liu,
685 and A. Namkhai (2000), The global soil moisture data bank, *Bull. Amer. Meteorol. Soc.*, 81,
686 1281–1299.

687 Seneviratne, S. I., and R. D. Koster (2012), A revised framework for analyzing soil moisture
688 memory in climate data: Derivation and interpretation, *J. Hydrometeorol.*, 13, 404–412.

689 Seneviratne, S. I., T. Corti, E. L. Davin, M. Hirschi, E. B. Jaeger, I. Lehner, B. Orlowsky, and
690 A. J. Teuling (2010), Investigating soil moisture-climate interactions in a changing climate: A
691 review, *Earth-Science Reviews*, 99, 125–161.

692 Seneviratne, S. I., et al. (2006), Soil moisture memory in AGCM simulations: Analysis of Global
693 Land-Atmosphere Coupling Experiment (GLACE) data, *J. Hydrometeorol.*, 7, 1090–1112.

694 Seneviratne, S. I., et al. (2012), The Rietholzbach research site: Analysis of 32-year hydrocli-
695 matological time series and 2003 drought at a Swiss pre-alpine catchment, *Water Resources
696 Research*, 48, W06,526.

697 Teuling, A. J., I. Lehner, J. W. Kirchner, and S. I. Seneviratne (2010a), Catchments as simple
698 dynamical systems: experience from a Swiss pre-alpine catchment, *Water Resources Research*,
699 46, W10,502.

700 Teuling, A. J., et al. (2010b), Contrasting response of European forest and grassland energy
701 exchange to heatwaves, *Nature Geoscience*, 3, 722–727.

702 Tirone, G. (2003), Stima del bilancio del carbonio di due ecosistemi forestali Mediterranei. Con-
703 fronto tra una lecceta e una pineta., Ph.D. thesis, University of Tuscia, Viterbo, Italy. [in Italian].

704 Twine, T. E., W. P. Kustas, J. M. Norman, D. R. Cook, P. R. Houser, T. P. Meyers, J. H. Prueger,
705 P. J. Starks, and M. L. Wesely (2000), Correcting eddy-covariance flux underestimates over a
706 grassland, *Agric. For. Meteorol.*, 103, 279–300.

707 Vinnikov, K. Y., and I. B. Yeserkepova (1990), Soil moisture: Empirical data and model results,
708 *J. Climate*, 4, 66–79.

709 Viterbo, P., and A. K. Betts (1999), Impact of the ECMWF reanalysis soil water on forecasts of
710 the July 1993 Mississippi flood, *J. Geophys. Res.*, 19, 361–366.

711 Wilson, K., et al. (2002), Energy balance closure at FLUXNET sites, *Agric. Forest Meteorol.*, 113,
712 223–243.

Table 1: Overview of step width of model parameters as used in the optimization procedure, of their boundaries and the range of their respective estimates.

Parameter	Step width	Lower limit	Upper limit	Maximum value found	Minimum value found
water holding capacity c_s (mm)	30	30	-	500	80
inverse streamflow recession timescale $\frac{1}{\tau}$ (1/days)	0.02	0.02	-	0.80	0.10
runoff ratio exponent α	0.2	0.2	-	8.0	0.8
ET ratio exponent γ	0.03	0.03	-	1.05	0.03
max ET ratio β_0	0.03	0.03	0.99	0.99	0.60

Table 2: Overview of measurements and conditions at the sites and catchments used for validating the model as well as references describing the sites in more detail.

Station	Data period	Land cover	Soil type	SM measurement depths (m)
Oensingen (CH)	2002 - 2007	grassland	clay	0.05, 0.1, 0.3, 0.5
Rietholzbach (CH)	1994 - 2007	grassland	(clay) loam	0.05, 0.15, 0.55
San Rossore (ITA)	2004 - 2010	forest	sand	0.1, 0.3, 0.45

Station	Streamflow station (distance and direction rel. to SM station in km)	Catchment area	Satellite radiation coordinates	Reference
Oensingen (CH)	Brugg (38 east)	11726km ²	47.5°N 7°E	<i>Ammann et al. 2010</i>
Rietholzbach (CH)	Mosnang (1.5)	3.3km ²	47.5°N 9°E	<i>Seneviratne et al. 2012</i>
San Rossore (ITA)	Vicopisano (25 east)	8228km ²	43.5°N 11°E	<i>Tirone 2003</i>

Table 3: Overview of catchments where the model is applied.

Catchment	Size (km ²)	Mean altitude (m above sea level)	Mean CTI	Mean daily streamflow (mm)	Satellite radiation coordinates
Aach	49	480	11.82	1.32	47.5°N 9°E
Broye	392	710	11.33	1.78	46.5°N 7°E
Cassarate	74	990	9.39	2.72	45.5°N 9°E
Emme	124	1189	10.03	3.01	46.5°N 7°E
Ergolz	261	590	10.99	1.25	47.5°N 7°E
Goldach	50	833	10.71	2.32	47.5°N 9°E
Guerbe	54	837	9.98	2.01	46.5°N 7°E
kleine Emme	477	1050	10.48	2.81	46.5°N 7°E
Langeten	60	766	11.37	1.79	47.5°N 7°E
Mentue	105	679	11.27	1.34	46.5°N 7°E
Murg	79	650	11.47	1.98	47.5°N 9°E
Sense	352	1068	10.5	2.18	46.5°N 7°E
Sitter	74	1252	10.18	4.06	47.5°N 9°E

Table 4: Overview of fitted parameters for all catchments.

	Catchment	water holding capacity c_s (mm)	inverse streamflow recession timescale $\frac{1}{\tau}$ (1/days)	runoff ratio exponent α	ET ratio exponent γ	max ET ratio β_0
Catchments in which model is validated	Oensingen	410	0.10	0.8	0.03	0.60
	Rietholzbach	140	0.80	4.4	0.42	0.99
	San Rossore	500	0.14	3.6	0.03	0.96
Catchments in which model is applied	Aach	230	0.62	8.0	0.78	0.99
	Broye	200	0.36	5.8	0.42	0.60
	Cassarate	410	0.36	6.8	0.33	0.81
	Emme	80	0.74	1.4	0.27	0.99
	Ergolz	290	0.54	5.6	0.90	0.99
	Goldach	350	0.60	6.8	0.75	0.99
	Guerbe	170	0.44	4.2	1.05	0.99
	kleine Emme	80	0.66	2.4	0.60	0.99
	Langeten	320	0.52	4.0	0.06	0.81
	Mentue	410	0.52	6.4	0.66	0.99
	Murg	230	0.50	6.2	0.63	0.99
	Sense	80	0.52	1.6	0.09	0.69
	Sitter	170	0.56	7.4	0.90	0.69

713 Figure 1: Soil moisture memory computed from observed and modeled soil moisture in the 3
714 validation catchments for lag times between 5 and 40 days. Values outside the plotting range of
715 the difference plots are shaded in gray.

716

717 Figure 2: Soil moisture memory computed for all possible combinations of meteorological forc-
718 ings and parameter sets from the 3 validation catchments as compared to observed soil moisture
719 memory displayed in the bottom row.

720

721 Figure 3: The top rows show modeled soil moisture, streamflow and evapotranspiration plotted
722 against observations for data within the period July-September that was used to fit the functions.
723 The red lines are fitted through least-squares regressions. The bottom row shows the functions
724 of Equations (2) (black) and (6) (red) fitted for each catchment. These are compared to weekly-
725 averaged observed corresponding ratios plotted as points against observed soil moisture (mean
726 and variance adapted to model soil moisture).

727

728 Figure 4: Fitted hydrographs (Equation (4)) in the 3 validation catchments.

729

730 Figure 5: Soil moisture memory of lag 30 days at all investigated catchments across Switzerland,
731 averaged from April through October. The brownish background indicates the topography, with
732 darker brown referring to higher altitudes.

733

734 Figure 6: Overview of fitted functions, soil moisture memory, its uncertainty (refer to text for
735 details), $\tilde{\kappa}_n = \frac{\sigma_{w_n,y}}{\sigma_{P_n,y} t_{lag}}$ and $\rho(w_n, P_n)$ (as described in Section 4.4.1) for all catchments going
736 from high soil moisture memory (top row) to low soil moisture memory (bottom row). In the left
737 hand side column the red curves correspond to the fitted runoff ratio functions, the black lines
738 show the fitted ET ratio functions and the vertical blue lines denote the 5% and 95% quantile of

₇₃₉ all soil moisture values in the time frame between April and October. Soil moisture memory, its
₇₄₀ uncertainty, $\tilde{\kappa_n}$ and $\rho(w_n, P_n)$ are computed for all months between April and October and for
₇₄₁ lag times between 5 and 40 days.

₇₄₂

₇₄₃ Figure 7: Continuation of Figure 6.

₇₄₄

₇₄₅ Figure 8: Correlations of fitted model parameters (listed in Table 1) at all catchments with re-
₇₄₆ spective soil moisture memory at a lag of 30 days. Dark gray corresponds to negative correlations,
₇₄₇ light gray indicates positive correlations. Hatching indicates correlations that are not significant
₇₄₈ on the 5% level (two-sided t-test).

₇₄₉

₇₅₀ Figure 9: The top row displays the soil moisture memories of lag 30 days of all 13 catchments
₇₅₁ plotted against altitude, CTI and dryness index including a least-squares fit and explained fraction
₇₅₂ of variance. The same is shown in the lower row for the ratio $\tilde{\kappa_n} = \frac{\sigma_{w_n,y}}{\sigma_{P_n,y} t_{lag}}$, also for a lag time
₇₅₃ of 30 days.

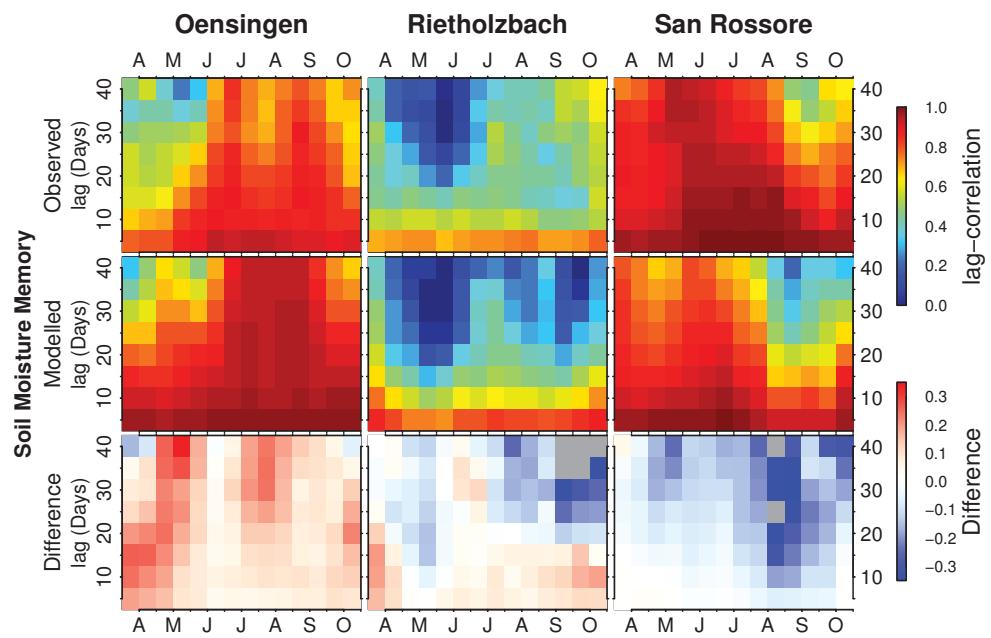


Figure 1: Soil moisture memory computed from observed and modeled soil moisture in the 3 validation catchments for lag times between 5 and 40 days. Values outside the plotting range of the difference plots are shaded in gray.

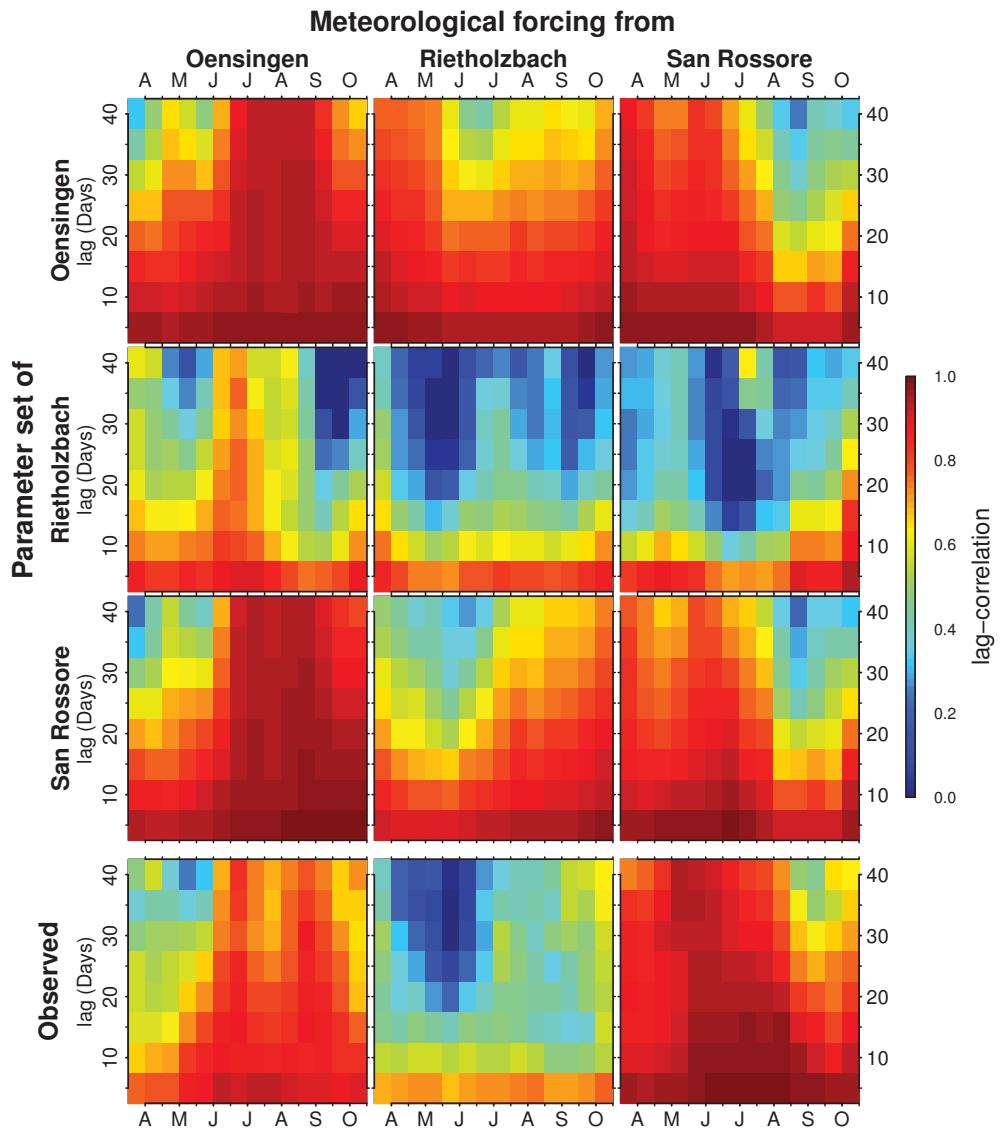


Figure 2: Soil moisture memory computed for all possible combinations of meteorological forcings and parameter sets from the 3 validation catchments as compared to observed soil moisture memory displayed in the bottom row.

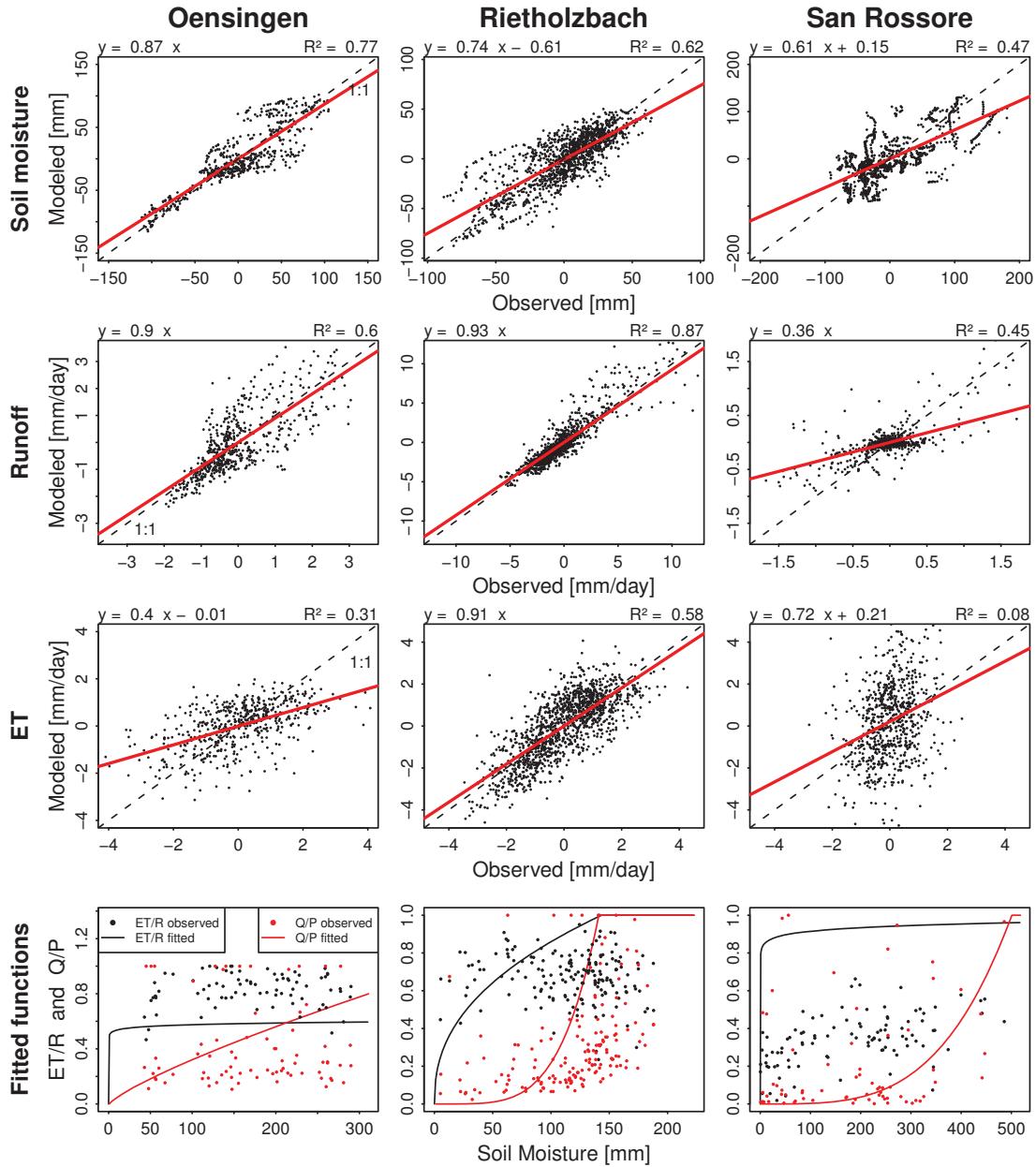


Figure 3: The top rows show modeled soil moisture, streamflow and evapotranspiration plotted against observations for data within the period July-September that was used to fit the functions. The red lines are fitted through least-squares regressions. The bottom row shows the functions of Equations (2) (black) and (6) (red) fitted for each catchment. These are compared to weekly-averaged observed corresponding ratios plotted as points against observed soil moisture (mean and variance adapted to model soil moisture).

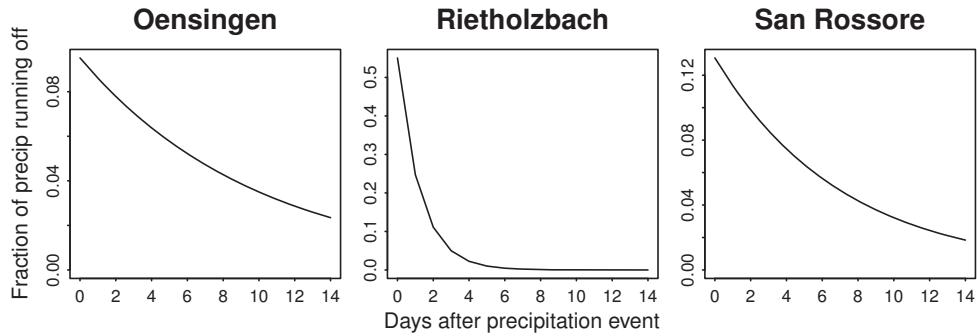


Figure 4: Fitted hydrographs (Equation (4)) in the 3 validation catchments.

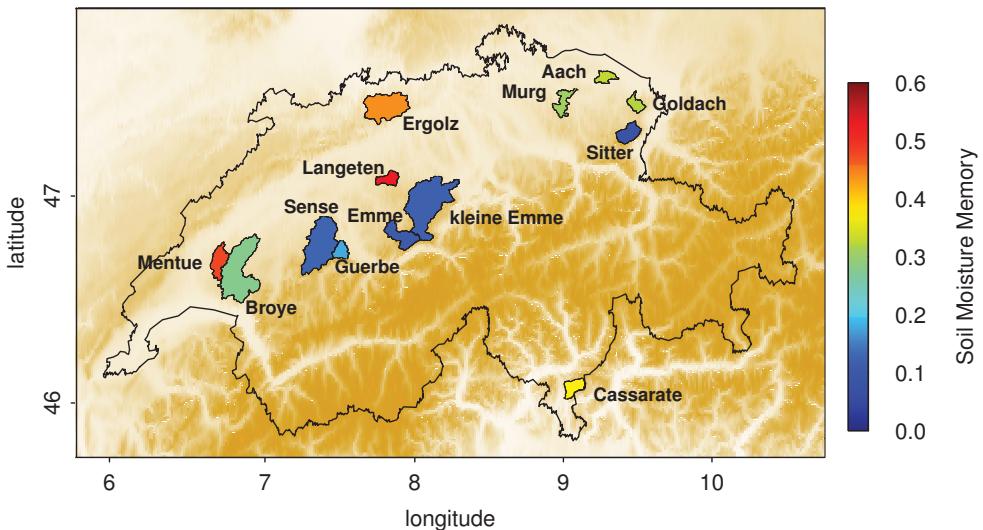


Figure 5: Soil moisture memory of lag 30 days at all investigated catchments across Switzerland, averaged from April through October. The brownish background indicates the topography, with darker brown referring to higher altitudes.

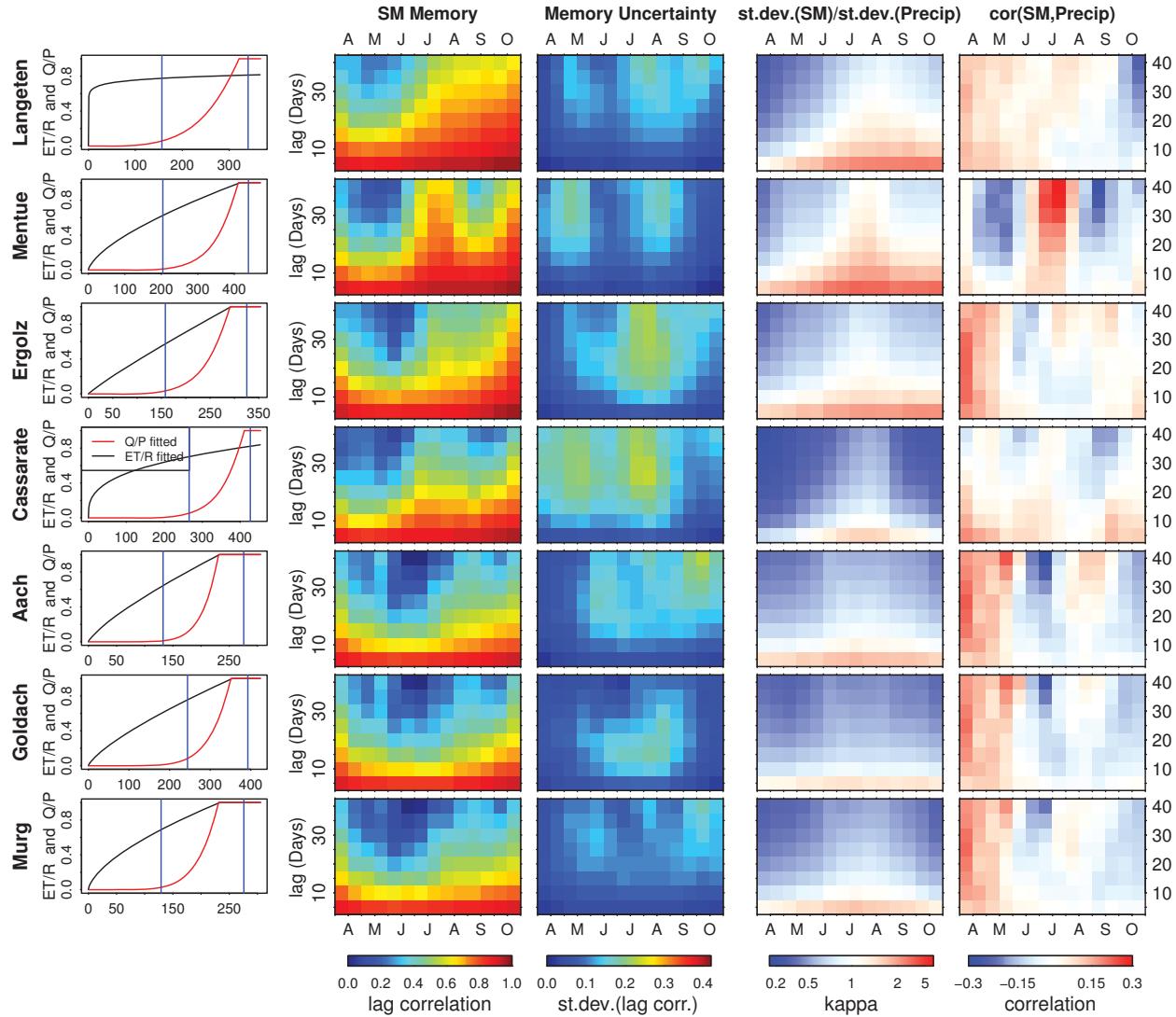
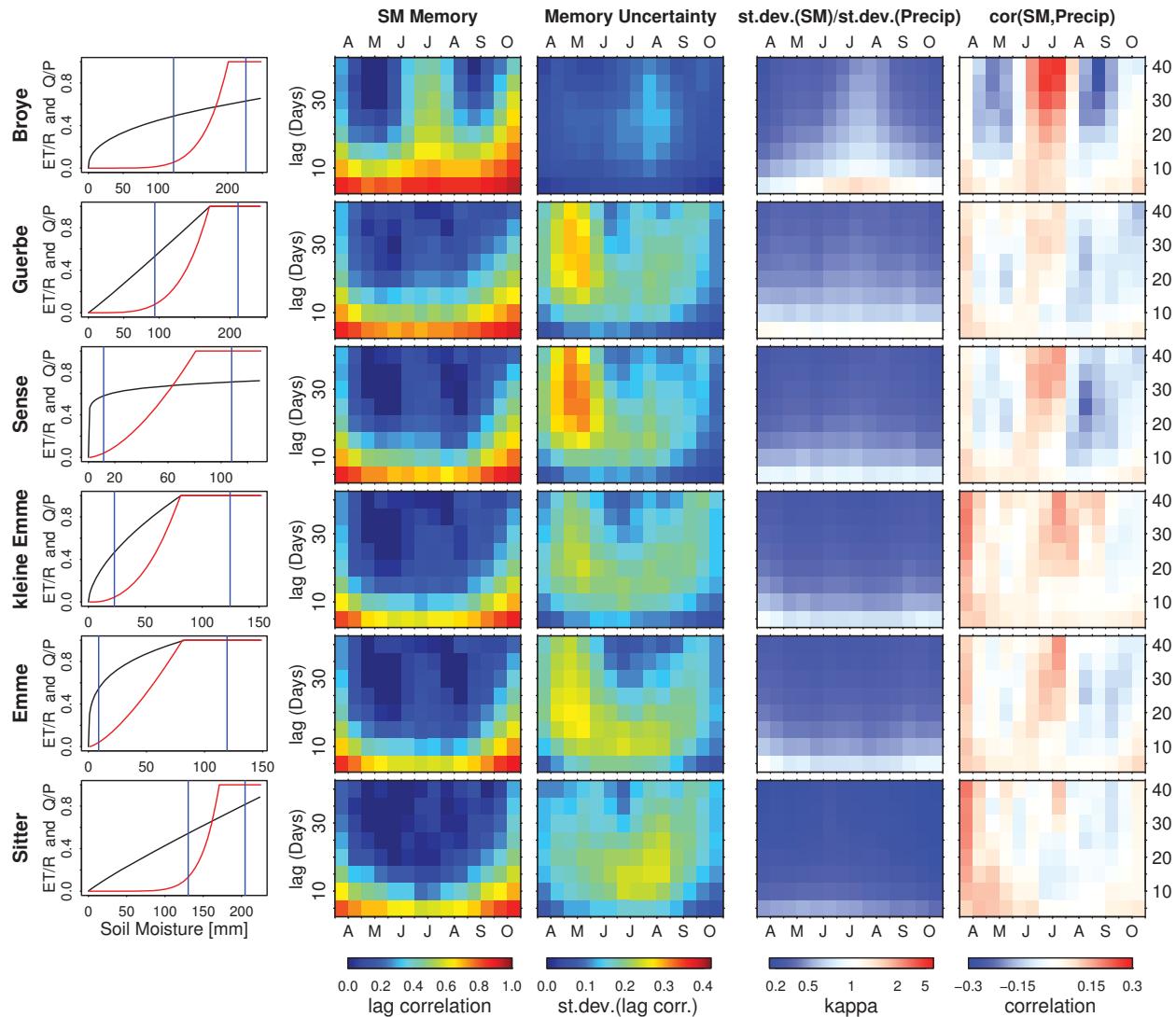


Figure 6: Overview of fitted functions, soil moisture memory, its uncertainty (refer to text for details), $\tilde{\kappa}_n = \frac{\sigma_{w_{n,y}}}{\sigma_{P_{n,y}t_{lag}}}$ and $\rho(w_n, P_n)$ (as described in Section 4.4.1) for all catchments going from high soil moisture memory (top row) to low soil moisture memory (bottom row). In the left hand side column the red curves correspond to the fitted runoff ratio functions, the black lines show the fitted ET ratio functions and the vertical blue lines denote the 5% and 95% quantile of all soil moisture values in the time frame between April and October. Soil moisture memory, its uncertainty, $\tilde{\kappa}_n$ and $\rho(w_n, P_n)$ are computed for all months between April and October and for lag times between 5 and 40 days.



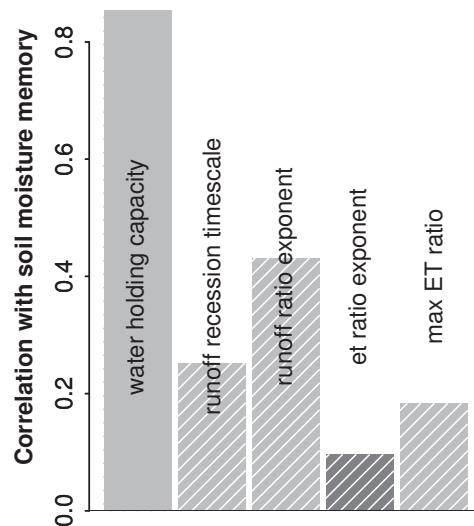


Figure 8: Correlations of fitted model parameters (listed in Table 1) at all catchments with respective soil moisture memory at a lag of 30 days. Dark gray corresponds to negative correlations, light gray indicates positive correlations. Hatching indicates correlations that are not significant on the 5% level (two-sided t-test).

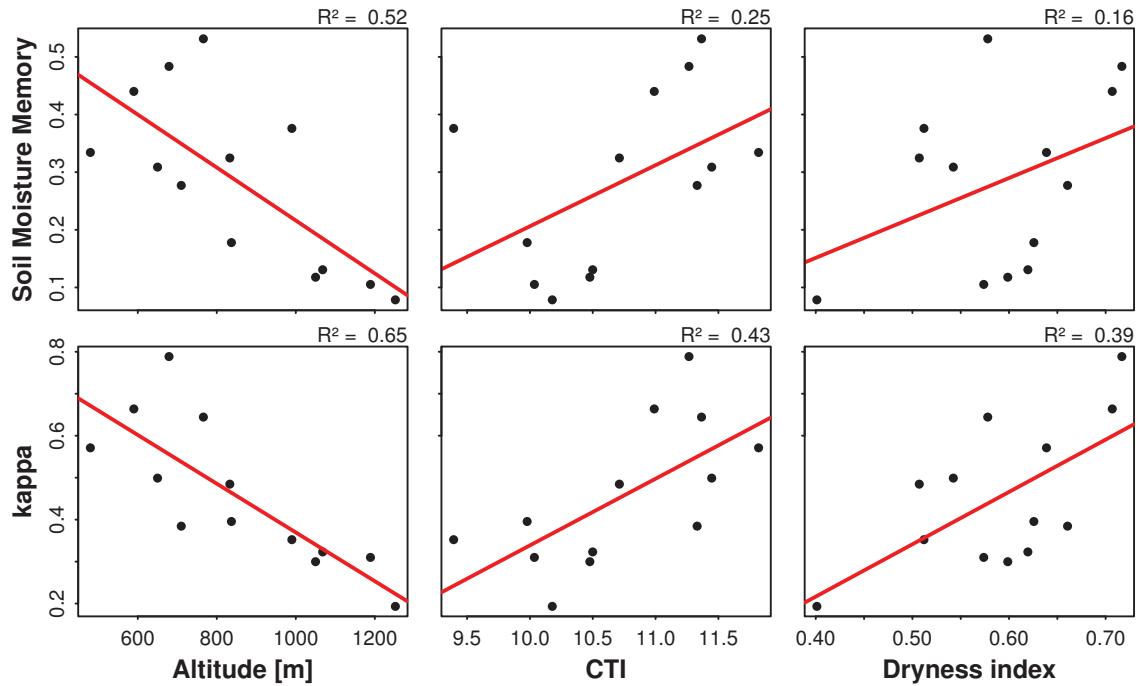


Figure 9: The top row displays the soil moisture memories of lag 30 days of all 13 catchments plotted against altitude, CTI and dryness index including a least-squares fit and explained fraction of variance. The same is shown in the lower row for the ratio $\tilde{\kappa}_n = \frac{\sigma_{w_{n,y}}}{\sigma_{P_{n,y} t_{lag}}}$, also for a lag time of 30 days.